Received October 15, 2016, accepted November 1, 2016, date of publication December 1, 2016, date of current version March 2, 2017.

Digital Object Identifier 10.1109/ACCESS.2016.2633723

Energy-Aware Power Control in Energy Cooperation Aided Millimeter Wave Cellular Networks With Renewable Energy Resources

BINGYU XU[1], YUE CHEN[1], (Senior Member, IEEE), JESÚS REQUENA CARRIÓN[1], (Senior Member, IEEE), JONATHAN LOO[2], (Member, IEEE), AND ALEXEY VINEL[3], (Senior Member, IEEE)

[1]School of Electronic Engineering and Computer Science, Queen Mary University of London, London, E1 4NS, U.K.
[2]School of Science and Technology, Middlesex University, London, NW4 4BT, U.K.
[3]School of Information Technology, Halmstad University, 301 18 Halmstad, Sweden

Corresponding author: B. Xu (bingyu.xu@qmul.ac.uk)

ABSTRACT Increased energy consumption becomes a major issue in 5G cellular networks, which inspires the network operators to deploy renewable energy sources. However, due to the fluctuating nature of renewable energy sources, the energy harvested by base stations (BSs) may not fit for their load conditions. The transmit power of the BS needs to be redesigned again. Hence, this paper considers power control in energy cooperation enabled millimeter wave networks, to alleviate the harvested energy imbalance problem and reduce the energy waste. Each BS is solely powered by renewable energy sources and the harvested energy is allowed to be transferred between BSs. Each BS needs to determine whether the energy should be stored in the battery or transferred to others at each time slot. In this paper, power control is formulated as a stochastic optimization problem, aiming at maximizing the time average network utility while keeping the network stable. An online algorithm called dynamic energy-aware power allocation is proposed based on Lyapunov optimization, which does not need to acquire any statistical knowledge of channels and traffic arrivals. Simulation results show that compared with the power control scheme without energy cooperation, the proposed algorithm with energy cooperation can achieve higher network sum rate while reducing the delay and the required battery capacity.

INDEX TERMS Energy cooperation, millimeter wave, power control, online algorithm.

I. INTRODUCTION

Nowadays, the enormous amount of data requirement pushes the limits of energy consumption in wireless communication networks. By 2020, there will be 50 billion connected devices [1]. Such vast level of connectivity will lead to an unprecedented surge in global energy consumption without effective energy management. According to the latest data, Information and Communications Technology (ICT) accounts for about 10% of the world's energy consumption [2]. In addition, the environmental issues such as carbon emissions are also critical. These stimulate more emerging technologies to be implemented to meet the energy saving targets. Energy harvesting technology is one of the viable solutions which can reduce both the carbon dioxide (CO_2) emission and the energy cost [3]. It can harvest green energy from ambiance such as solar panels and wind turbines to power base stations (BSs).

Although energy harvesting is a viable solution for reducing energy consumption of cellular networks, it also brings challenges to resource allocation and wireless network architecture designs [4]. Due to the fluctuating nature of renewable energy sources, the renewable energy harvested at BSs may not be adequate to meet their load conditions and it is critical to explore new resource allocation schemes for green 5G wireless networks. In general, based on the characteristics of the energy harvester and the impact of the surrounding environment, the resource allocation model for renewable energy powered wireless networks can be offline (deterministic) or online (stochastic). An online algorithm is triggered by energy arrivals or channel status variations (if any) and decisions on transmission policy have to be made based on only causal (the output only depends on the past and current inputs) information about the energy harvesting process during the transmissions. While full knowledge is known for the energy and data arrival rate by transmitters in offline scenarios, offline schemes are always the starting points of most research works in this area and provide the performance upper bounds for online schemes. Therefore, this paper focuses on the online scheme in energy cooperation enabled millimeter wave (mmWave) networks with renewable energy harvesting.

A. PRIOR WORK AND MOTIVATION

Considerable research efforts have been devoted to address the resource allocation problem with energy harvesting in the point-to-point scenario. In [5], packet scheduling problem is considered to minimize the transmission completion time in a fading channel. The work of [6] aims to adaptively change the transmission rate based on the traffic load and available energy in a single-user wireless communication system. It considers both all bits arrived before the transmission starts and bits arrive during the transmissions these two scenarios. A recursive geometric waterfilling algorithm is proposed in [7] for power control with a sum power constraint. It targets to maximize the throughput in a fading channel. Huang *et al.* [8] study the optimal power allocation problem to minimize the outage probability in point-to-point fading channels. For online scenarios, the work of [4] uses stochastic dynamic programming to maximize the throughput by a deadline under stochastic fading with causal channel state feedback, and the capacity of the battery is limited in this wireless fading channel. Using dynamic programming to maximize the throughput is also considered in [9]. This contribution optimizes the energy allocation over a finite time horizon and studies the structure of the maximum throughput and the corresponding optimal energy allocation solution, including concavity and monotonicity. Meanwhile, there are also other works for maximizing the average reward rate in terms of message values [10] and minimizing the estimation error covariance [11].

The implementation of energy harvesting in multi-user systems has been considered in [12]–[14]. In [12], the optimal packet scheduling problem is considered in an offline two-user system, and each user has an energy harvester. The goal is to minimize the average transmission time to the receiver by optimizing the transmit powers and transmission rates of two users. It develops an iterative waterfilling algorithm to acquire the departure region and solves the problem by convex optimization. Meanwhile, the existing works also consider the scenario with multiple users [13], [14]. In [13], the sum-rate of an N-user fading channel is maximized under the constraints of the battery capacity and the maximum energy consumption. The formulated convex optimization problem is solved by the iterative water-filling algorithm. In [14], the transmit powers and transmission rates are optimized to minimize the transmission completion time in an additive white gaussian noise (AWGN) broadcast channel. The core idea of [14] is that the total power can be optimally split based on a cut-off power level, and accordingly an algorithm is proposed to find the global optimal policy.

Meanwhile, recent works such as [15]–[21] have focused on energy harvesting enabled cellular networks. In [15], power control is studied in device-to-device (D2D) enabled cellular networks and aims to maximize the overall throughput. In order to minimize the grid energy consumption, a green energy optimization problem is addressed in [16]. A sub-carrier and power allocation scheme in downlink OFDMA downlink networks is proposed in [17], so as to maximize the energy efficiency of the network while the storage of each BS is finite. The formulated offline problem of [17] is solved by fractional programming and Lagrange dual analysis. In [18], The average grid power consumption minimization problem is formulated by optimizing the BS sleeping policy, subcarriers allocation and renewable energy allocation. The formulated problem is solved in two steps and a two-stage dynamic programming algorithm is established. A two-timescale delay optimal transmission control and user association problem for downlink coordinated MIMO systems is proposed in [19]. It formulates the problem as a partially observed Markov decision problem and acquires a delay-aware distributed solution to reduce the complexity. Han and Ansari [20] propose a distributed user association scheme called Green-energy Aware and Latency Aware (GALA) in HetNets, which can decrease the on-grid power consumption and the average traffic delivery latency. The power control problem is considered in [16]. This work seeks to find the optimal pilot signal power and the coverage area of each BS in order to minimize the overall on-grid energy consumption. In [21], a joint bandwidth and power allocation approach for both uplink and downlink is proposed to maximize energy efficiency for both UEs and network operators.

Although batteries can store the extra harvested energy for later use in renewable energy harvesting networks, some BSs may always have abundant harvested energy (e.g., better sunshine conditions) and these energy is wasted, while other BSs' harvested energy is insufficient. Besides, the deployment of BSs with large energy storage brings high expenditure of the networks [22]. Hence, the use of storage solely cannot solve the energy fluctuating problem. With the recent development of the smart grid that enables both two-way information and energy flows, the concept of energy cooperation is introduced to mitigate the energy imbalance problem [23]. Energy cooperation allows energy to be shared between BSs with some energy waste through the energy transmission process. By this way, BSs can send its excessive energy to BSs whose energy are deficient. In addition, it can reduce the required battery capacity which can diminish the capital expenditures (CAPEX).

Energy cooperation in renewable energy harvesting enabled cellular networks has attracted recent attention. In [22], the joint spectrum and energy cooperation between two BSs in two neighboring cellular systems was studied to minimize the energy cost through power control and spectrum allocation. Then, the paper considers a partially cooperative scenario where the BSs have their own interests.

The joint communication and energy cooperation is studied in [24] and [25]. In [24], all BSs can trade energy via the aggregator in the smart grid with different prices in order to minimize the total energy cost. In [25], information and energy are assumed to be transferred between BSs via the smart grid, and the power control problem is formulated as an optimization problem to maximize the sum rate of the system. The energy trading problem is also studied in [26], with the objective of minimizing the time average cost of energy exchange between two BSs. The formulated stochastic optimization problem in [26] is solved by Lyapunov optimization. Lyapunov optimization is a useful technique to solve stochastic optimization problems. It does not demand any statistical knowledge of the channel, traffic and energy, which can be used for power control and routing algorithms [27].

In fifth generation (5G) wireless networks, mmWave is one of the key technologies to deliver higher data rates and lower latency [28]. It owns a huge swath of spectrum between 30 GHz and 300 GHz to shift wireless transmissions away from the current bandwidth-limited networks. However, compared with conventional cellular networks, higher propagation loss and the use of large number of antennas in mmWave networks give rise to high energy consumption. Therefore, renewable energy harvesting in mmWave networks is an appealing solution for reducing the energy cost.

B. CONTRIBUTIONS AND ORGANIZATION

While there are many prior works concerning resource allocation in energy cooperation enabled radio access networks, the energy management problem in mmWave networks is open. The unique features of mmWave channel including different propagation laws and sensitivity to blockages have a significant effect on the energy management. The conventional energy management designs are unsuitable for mmWave networks, due to the ignorance of mmWave channel characteristics. To the best of our knowledge, energy management in energy cooperation enabled mmWave networks has not been studied yet. Motivated by these, in this paper, we study the energy management problem in energy cooperation enabled mmWave cellular networks. By considering the stochastic traffic and energy arrivals, we formulate a stochastic optimization problem to maximize the time average throughput of the total network. We propose an online algorithm based on Lyapunov optimization. The main contributions of this paper are summarized as follows.

- We formulate a downlink optimization problem for optimizing the harvested energy, transmit powers and the transferred energy among BSs in a mmWave cellular network, to maximize the network utility while keeping the network stable such that the network backlog is bounded and the required battery capacity is finite. Each BS is solely powered by renewable energy sources, and the data and energy arrival rates are stochastic.
- Based on the Lyapunov optimization technique, we propose an online Dynamic Energy-aware Power Allocation (DEPA) algorithm to solve the formulated problem. Then, we analyze the performance of the proposed DEPA algorithm. It is confirmed that when the appropriate value of perturbation is selected, the proposed algorithm satisfies the network stability. The data queue and the required energy storage capacity keep in a low level.
- Finally, we investigate the performance of the proposed algorithm through simulations. The impacts of BS numbers, energy transfer efficiency and a control variable used for Lyapunov optimization are illustrated.

The remainder of the paper is organized as follows. Section II presents the system model and formulates the optimization problem. Section III gives the Lyapunov analysis and proposes the DEPA algorithm. After that, we present our simulation results in Section IV. Finally, Section V gives conclusions.

II. NETWORK MODEL AND PROBLEM FORMULATION

In this section, the system model of energy cooperation in mmWave networks is presented which has not been investigated before and the power control problem in energy cooperation enabled mmWave networks is formulated.

A. NETWORK DOWNLINK MODEL

As shown in Fig. 1 of this paper, we model a downlink energy cooperation enabled mmWave cellular network, where BSs are solely powered by renewable energy sources,[1] and energy can be shared between BSs through smart grid. In such a network, there are M mmWave BSs denoted as $BS_j, j \in \{1, 2, \ldots, M\}$ that share the same spectrum, and users are randomly located. User association is assumed to be already implemented before the power allocation, and there are N_j user equipments (UEs) denoted as UE_j^i $(i \in \{1, 2, \ldots, N_j\})$ served by BS_j. All BSs and users are equipped with directional antennas, and the antenna gains achieved by each BS and user are G_b and G_u, respectively.

Due to the use of higher frequencies and directional transmissions, mmWave cellular networks tend to be noise-limited [28]–[30], which means that the interference between BSs can be negligible. Thus, under the framework of the Shannon equation, the theoretical downlink data rate of a user i connected to the BS j at time slot t is given by

$$R_{ij}(t) = (N_j)^{-1}\log_2\left(1 + \frac{P_j(t)\, L_{ij}\left(d_{ij}\right) G_\mathrm{b} G_\mathrm{u}}{\sigma_o^2}\right), \quad (1)$$

where $P_j(t)$ is the transmit power of BS j at time t, σ_o^2 is the noise power level. $L_{ij}\left(d_{ij}\right)$ is the path loss between the user i and its associated BS j with a distance d_{ij}. Each user receives

[1] In this paper, to focus on the power control and energy cooperation problem, we do not make a specific assumption of the type of the renewable energy sources being used.

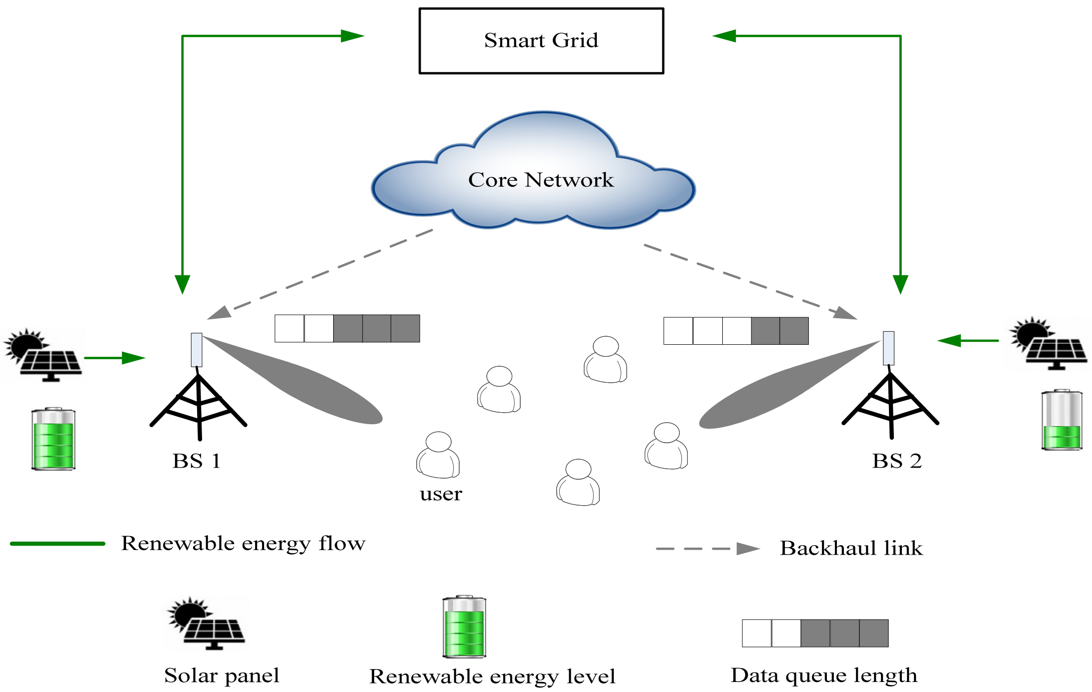


FIGURE 1. An example of an energy cooperation enabled mmWave cellular network powered by solar panels.

$(N_j)^{-1}$ of all the spectrum of BS j and the overall spectrum of BS j is normalized to 1. The channel is regarded as static and the data rate is considered as time-averaged. The path loss laws are different in line-of-sight (LOS) and non-line-of-sight (NLOS) conditions. In this paper, the mmWave path loss model proposed in [30] is employed and each mmWave link can be in one of three conditions: LOS, NLOS or outage.

The unit size of time is "slots" and the amount of transmitted data between user i and BS j in time slot t is $R_{ij}(t) \times (1\ \text{slot})$. Here, we omit the implicit multiplication by 1 time slot when converting between the data rate and the amount of data that transmit from the queue per time slot as suggested in [31]. In the same manner, the unit of the $P_j(t)$ is joule when converting between power and energy. As such, the transmitted data of the whole network at the time t is given by

$$U(t) = \sum_{j=1}^{M} \sum_{i=1}^{N_j} R_{ij}(t) \tag{2}$$

B. USER'S TRAFFIC AND DATA QUEUE MODEL

We assume that the data traffic required by the user is stochastic. The amount of data traffic arrival for user i served by BS j during time slot t is $D_{ij}(t)$. Let $D_{\max}$ denote the maximum allowable data traffic arrival rate per user due to backhaul capacity constraint, then we have

$$0 \le D_{ij}(t) \le D_{\max}, \forall i, j, t. \tag{3}$$

Based on the downlink data rate and traffic arrival rate, the data queue length $Q_{ij}(t)$ for user i served by BS j evolves as follows:

$$Q_{ij}(t+1) = [Q_{ij}(t) - R_{ij}(t)]^+ + D_{ij}(t), \quad \forall i \in \mathcal{U},\ j \in \mathcal{B}, \tag{4}$$

where $[x]^+ = \max\{0, x\}$. At the beginning, we assume $Q_{ij}(0) = 0, \forall i,\ j$.

C. ENERGY COOPERATION AND ENERGY QUEUE MODEL

Each BS stores the energy harvested from renewable energy sources and transferred energy from other BSs in its battery. At time t, the available energy at BS j is $E_j(t)$, and the amount of BS j's energy harvested from renewable energy sources is $e_j(t)$. We assume that there exists the maximum value $e_{\max}$ for harvesting renewable energy during the day, i.e., $e_j(t) \le e_{\max} < \infty, \forall j, t$. We assume that the energy can be exchanged among BSs through the smart grid. The transferred energy from BS j to BS j' is $\varepsilon_{jj'}(t)$. Since the energy storage at each BS is limited, the total transferred energy from BS j to other BSs satisfies $\sum_{j'=1, j' \neq j}^{M} \varepsilon_{jj'}(t) \le \varepsilon_{\max}^{(\text{out})} < \infty, \forall j, t$, and total transferred energy received at BS j satisfies $\sum_{j'=1, j' \neq j}^{M} \beta \varepsilon_{j'j}(t) \le \varepsilon_{\max}^{(\text{in})} < \infty, \forall j, t$. $\varepsilon_{\max}^{(\text{in})}$ and $\varepsilon_{\max}^{(\text{out})}$ are the maximum energy can be transferred from/to each BS respectively. Here, $\beta \in [0, 1]$ is the energy transfer efficiency between two BSs. The larger this value, the smaller energy loss in the energy exchange process. Considering the fact that total energy consumed by each BS should not exceed the total power supply including the harvested energy and the transferred energy, we have the following power consumption constraint at time t:

$$P_j(t) \le E_j(t) + \sum_{j'=1, j' \ne j}^{M} \beta \varepsilon_{j'j}(t) - \sum_{j'=1, j' \ne j}^{M} \varepsilon_{jj'}(t), \quad \forall t, \forall j \in \mathcal{B}. \tag{5}$$

The transmit energy of BS j at time t is $P_j(t) \times (1 \text{ slot})$, and we omit the implicit multiplication by 1 time slot of the $P_j(t)$ when converting between power and energy. Under this constraint, the energy queue length evolves as follows:

$$E_j(t+1) = E_j(t) - P_j(t) + e_j(t) + \sum_{j'=1, j' \ne j}^{M} \beta \varepsilon_{j'j}(t) - \sum_{j'=1, j' \ne j}^{M} \varepsilon_{jj'}(t). \tag{6}$$

D. PROBLEM FORMULATION

We propose an online algorithm to maximize the time average network utility while keeping the network stable. The utility of an user i connected to the BS j is $R_{ij}(t)$. The variables we optimized are transmit powers of BSs $P_j(t)$, the harvested energy $e_j(t)$ and energy transferred between BSs $\varepsilon_{jj'}(t)$ at every time slot. Then, the problem is formulated as

$$\begin{aligned}
&\max \lim_{T \to \infty} \sup \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[U(t)] \\
&\text{s.t. C1}: \lim_{T \to \infty} \sup \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\left[\sum_{j=1}^{M} \sum_{i=1}^{N_j} Q_{ij}(t)\right] < \infty, \\
&\quad \text{C2}: \lim_{T \to \infty} \sup \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\left[\sum_{j=1}^{M} E_j(t)\right] < \infty, \\
&\quad \text{C3}: P_j(t) \le E_j(t) + \sum_{j'=1, j' \ne j}^{M} \beta \varepsilon_{j'j}(t) \\
&\qquad - \sum_{j'=1, j' \ne j}^{M} \varepsilon_{jj'}(t), \forall t, \forall j, \\
&\quad \text{C4}: P_j(t) \le P_{\max}, \forall t, \forall j, \\
&\quad \text{C5}: e_j(t) \ge 0, P_j(t) \ge 0, \varepsilon_{j'j}(t) \ge 0, \forall t, \forall j, j', j \ne j', \\
&\text{var. } e_j(t), P_j(t), \varepsilon_{j'j}(t), \quad \forall t,
\end{aligned} \tag{7}$$

where $\mathbb{E}[\cdot]$ represents the expectation that is taken over the potential randomness of the channel and energy states and control decision at time t [27]. Constraint (C1) ensures that the length of data queue is bounded to avoid an intolerant delay. (C2) ensures that the length of energy queue is bounded such that we only need finite battery capacity. (C3) is the energy consumption constraint, which means the energy of each BS obtained from renewable energy sources and other BSs should greater than the consumption of it. (C4) is the maximum BS transmit power constraint, and (C5) makes sure that powers are non-negative. In the next section, we will show how we solve the formulated stochastic problem by Lyapunov optimization technique.

III. ALGORITHM DESIGN BASED ON LYAPUNOV OPTIMIZATION

In this section, we develop an online algorithm for solving the stochastic optimization problem (7) with the help of Lyapunov optimization. Compared with the conventional methods such as Markov decision processes and dynamic programming, Lyapunov optimization only needs the knowledge of the traffic and energy arrivals of the current time slot, which is a useful method for solving stochastic optimization problems [26].

A. LYAPUNOV OPTIMIZATION

Firstly, the Lyapunov function is defined as

$$L(t) = \frac{1}{2} \sum_{j=1}^{M} \sum_{i=1}^{N_j} \left(Q_{ij}(t)\right)^2 + \frac{1}{2} \sum_{j=1}^{M} \left(E_j(t) - \theta_j\right)^2, \tag{8}$$

where θ_j is a perturbation. By adding a perturbation, It can ensure that there are always enough energy in the energy queue for transmission. The Lyapunov function is used to measure the data and energy flow in the system.

The Lyapunov drift is used to measure the expected difference for the Lyapunov function between the time slot t and $(t+1)$. Let $Z(t) = [Q(t), E(t)]$ with $Q(t) = [Q_{ij}(t)]$ and $E(t) = [E_j(t)]$, the one-time conditional Lyapunov drift is given by

$$\Delta(t) = \mathbb{E}\Big[L(t+1) - L(t) | Z(t)\Big]. \tag{9}$$

In addition, considering the objective function of problem (7), the drift-plus-penalty is defined as

$$\Delta_V(t) = \Delta(t) \underbrace{-V\mathbb{E}\Big[\sum_{j=1}^{M} \sum_{i=1}^{N_j} R_{ij}(t) | Z(t)\Big]}_{\text{Penalty term}}. \tag{10}$$

In (10), V is a non-negative control variable which represents the relative importance of minimizing the energy and data queue length to a lower level and maximizing the sum rate of the whole network. The upper bound of the drift-plus-penalty is derived as follows.

Lemma 1: For any feasible values of $e_j(t)$, $P_j(t)$, $\varepsilon_{j'j}(t)$, V and $Z(t)$ at time t, the drift-plus-penalty is upper bounded as

$$\Delta_V(t) \le A - \sum_{j=1}^{M}\sum_{i=1}^{N_j} Q_{ij}(t)\,\mathbb{E}\left[\left(R_{ij}(t) - D_{ij}(t)\right) \mid Z(t)\right] - \sum_{j=1}^{M}\left(E_j(t)-\theta_j\right)\mathbb{E}\Big[P_j(t) - e_j(t) + \sum_{j'=1, j'\neq j}^{M} \varepsilon_{jj'}(t) - \sum_{j'=1, j'\neq j}^{M} \beta\varepsilon_{j'j}(t) \mid Z(t)\Big] - V\mathbb{E}\Big[\sum_{j=1}^{M}\sum_{i=1}^{N_j} R_{ij}(t) \mid Z(t)\Big], \tag{11}$$

where A is a positive constant value satisfying

$$A \ge \frac{\sum_{j=1}^{M}\sum_{i=1}^{N_j} D_{\max}}{2} + \sum_{j=1}^{M}\sum_{i=1}^{N_j}\mathbb{E}\left[\frac{\left(R_{ij}(t)\right)^2}{2} \mid Z(t)\right] + M\frac{\left(P_{\max}+\varepsilon_{\max}^{(\text{out})}\right)^2 + \left(e_{\max}+\varepsilon_{\max}^{(\text{in})}\right)^2}{2}. \tag{12}$$

Proof: To obtain the upper bound of the drift-plus-penalty $\Delta_V(t)$, we first need to calculate the difference for the Lyapunov function between the time slot t and $t+1$, i.e.,

$$L(t+1) - L(t) = \underbrace{\sum_{j=1}^{M}\sum_{i=1}^{N_j}\frac{\left(Q_{ij}(t+1)\right)^2 - \left(Q_{ij}(t)\right)^2}{2}}_{\Theta_1} + \underbrace{\sum_{j=1}^{M}\frac{\left(E_j(t+1)-\theta_j\right)^2 - \left(E_j(t)-\theta_j\right)^2}{2}}_{\Theta_2}. \tag{13}$$

Based on (4), the square of the data queue for user i served by BS j at time $t+1$ is upper bounded as

$$\left(Q_{ij}(t+1)\right)^2 \le \left(Q_{ij}(t)\right)^2 + \left(R_{ij}(t)\right)^2 + \left(D_{ij}(t)\right)^2 - 2Q_{ij}(t)\left(R_{ij}(t) - D_{ij}(t)\right). \tag{14}$$

By summing (14) over all i and j, we have

$$\begin{aligned}\Theta_1 &\le \sum_{j=1}^{M}\sum_{i=1}^{N_j}\frac{\left(R_{ij}(t)\right)^2 + \left(D_{ij}(t)\right)^2}{2} - \sum_{j=1}^{M}\sum_{i=1}^{N_j} Q_{ij}(t)\left(R_{ij}(t)-D_{ij}(t)\right)\\ &\overset{(a)}{\le} \frac{\sum_{j=1}^{M}\sum_{i=1}^{N_j} D_{\max}}{2} + \sum_{j=1}^{M}\sum_{i=1}^{N_j}\frac{\left(R_{ij}(t)\right)^2}{2} - \sum_{j=1}^{M}\sum_{i=1}^{N_j} Q_{ij}(t)\left(R_{ij}(t)-D_{ij}(t)\right),\end{aligned} \tag{15}$$

where (a) is obtained by using the backhaul capacity constraint in (3). Then, considering energy queue given by (6), the square of the energy queue for user i served by BS j at time $t+1$ is upper bounded as

$$\begin{aligned}&\left(E_j(t+1)-\theta_j\right)^2\\ &\le \left(E_j(t)-\theta_j\right)^2 + \Big(P_j(t) + \sum_{j'=1, j'\neq j}^{M}\varepsilon_{jj'}(t)\Big)^2 + \Big(e_j(t) + \sum_{j'=1, j'\neq j}^{M}\beta\varepsilon_{j'j}(t)\Big)^2 - 2\left(E_j(t)-\theta_j\right)\\ &\quad\times\left(P_j(t)-e_j(t)\right) - 2\left(E_j(t)-\theta_j\right)\\ &\quad\times\Big(\sum_{j'=1, j'\neq j}^{M}\varepsilon_{jj'}(t) - \sum_{j'=1, j'\neq j}^{M}\beta\varepsilon_{j'j}(t)\Big)\\ &\le \left(E_j(t)-\theta_j\right)^2 + \left(P_{\max}+\varepsilon_{\max}^{(\text{out})}\right)^2 + \left(e_{\max}+\varepsilon_{\max}^{(\text{in})}\right)^2 - 2\left(E_j(t)-\theta_j\right)\left(P_j(t)-e_j(t)\right)\\ &\quad - 2\left(E_j(t)-\theta_j\right)\Big(\sum_{j'=1, j'\neq j}^{M}\varepsilon_{jj'}(t) - \sum_{j'=1, j'\neq j}^{M}\beta\varepsilon_{j'j}(t)\Big).\end{aligned} \tag{16}$$

By summing (16) over all j, we have

$$\begin{aligned}\Theta_2 \le{}& M\frac{\left(P_{\max}+\varepsilon_{\max}^{(\text{out})}\right)^2 + \left(e_{\max}+\varepsilon_{\max}^{(\text{in})}\right)^2}{2}\\ &- \sum_{j=1}^{M}\left(E_j(t)-\theta_j\right)\left(P_j(t)-e_j(t)\right) - \sum_{j=1}^{M}\left(E_j(t)-\theta_j\right)\\ &\times\Big(\sum_{j'=1, j'\neq j}^{M}\varepsilon_{jj'}(t) - \sum_{j'=1, j'\neq j}^{M}\beta\varepsilon_{j'j}(t)\Big).\end{aligned} \tag{17}$$

Based on (15) and (17), the one-time conditional Lyapunov drift $\Delta(t)$ is upper bounded as

$$\begin{aligned}&\Delta(t)\\ &\le A - \sum_{j=1}^{M}\sum_{i=1}^{N_j} Q_{ij}(t)\,\mathbb{E}\left[\left(R_{ij}(t)-D_{ij}(t)\right) \mid Z(t)\right]\\ &\quad - \sum_{j=1}^{M}\left(E_j(t)-\theta_j\right)\mathbb{E}\Big[P_j(t) - e_j(t) + \sum_{j'=1, j'\neq j}^{M}\varepsilon_{jj'}(t)\\ &\quad - \sum_{j'=1, j'\neq j}^{M}\beta\varepsilon_{j'j}(t) \mid Z(t)\Big],\end{aligned} \tag{18}$$

where A satisfies

$$A \geq \frac{\sum_{j=1}^{M}\sum_{i=1}^{N_j} D_{\max}}{2} + \sum_{j=1}^{M}\sum_{i=1}^{N_j}\mathbb{E}\left[\frac{(R_{ij}(t))^2}{2} \mid Z(t)\right] + M\frac{\left(P_{\max}+\varepsilon_{\max}^{(\text{out})}\right)^2+\left(e_{\max}+\varepsilon_{\max}^{(\text{in})}\right)^2}{2}. \quad (19)$$

Substituting (18) into (10), we get the upper bound of the drift-plus-penalty $\Delta_V(t)$, and complete the proof. □

Base on the stochastic optimization introduced in [32, Ch. 4], the control decision is made at every time t for minimizing the upper bound of drift-plus-penalty given in the right-hand-side (RHS) of (11). Note that the penalty term $-V\mathbb{E}\left[\sum_{j=1}^{M}\sum_{i=1}^{N_j} R_{ij}(t)|Z(t)\right]$ in (11) is used to seek balance between minimizing queue length drift and maximizing the network utility, and larger V represents that increasing the data rate is more essential. Therefore, by removing the expectation operations and constant terms in the RHS of (11), an optimization problem needs to be solved at time t, which is as follows:

$$\begin{aligned}\max_{e(t),P(t),\boldsymbol{\varepsilon}(t)} & \sum_{j=1}^{M}\sum_{i=1}^{N_j} Q_{ij}(t)R_{ij}(t) - \sum_{j=1}^{M}\left(E_j(t)-\theta_j\right)e_j(t) \\ & + \sum_{j=1}^{M}\left(E_j(t)-\theta_j\right)\Bigg(P_j(t) + \sum_{j'=1,j'\neq j}^{M}\varepsilon_{jj'}(t) \\ & - \sum_{j'=1,j'\neq j}^{M}\beta\varepsilon_{j'j}(t)\Bigg) + V\sum_{j=1}^{M}\sum_{i=1}^{N_j}R_{ij}(t) \quad (20)\\ \text{s.t. } & \text{C3, C4, C5.}\end{aligned}$$

Since the objective is to maximize (20), there will be no energy harvesting at BS j when $E_j(t) > \theta_j$, i.e. $e_j(t) = 0$. This also ensures that the energy storage of each BS is finite (more details will be illustrated in the following subsection). After the energy harvesting decision, the power allocation policy $(P(t), \boldsymbol{\varepsilon}(t))$ at time t is given by solving the following problem:

$$\begin{aligned}\max_{P(t),\boldsymbol{\varepsilon}(t)} & \sum_{j=1}^{M}\sum_{i=1}^{N_j} Q_{ij}(t)R_{ij}(t) + \sum_{j=1}^{M}\left(E_j(t)-\theta_j\right)\Bigg(P_j(t) \\ & + \sum_{j'=1,j'\neq j}^{M}\varepsilon_{jj'}(t) - \sum_{j'=1,j'\neq j}^{M}\beta\varepsilon_{j'j}(t)\Bigg) \\ & + V\sum_{j=1}^{M}\sum_{i=1}^{N_j}R_{ij}(t) \quad (21)\\ \text{s.t. } & \text{C3, C4, C5.}\end{aligned}$$

It can be seen that the objective function of problem (21) is concave and the constraint functions are affine, which can be solved by existing convex optimization softwares such as CVX [33]. Base on the stochastic optimization introduced in [32], problem (21) is equivalent to (7) and the original problem is solved. Finally, we obtain the proposed DEPA algorithm for solving our stochastic optimization problem (7), which is shown in Algorithm 1.

Algorithm 1 Dynamic Energy-aware Power Allocation (DEPA) Algorithm

1: **if** $t = 0$, **then**
2: **Intialize** the perturbation vector $\boldsymbol{\theta}$.
Observe the data queue length $Q_{ij}(t)$ and the energy queue length $E_j(t)$, $\forall i, j$.
3: **else**
4: **repeat**
5: Energy harvesting decision:
BS j harvests energy when $E_j(t) \leq \theta_j$, $\forall j$.
6: Power control decision:
Obtain $(P(t), \boldsymbol{\varepsilon}(t))$ by solving (21) using CVX.
7: $t = t + 1$.
8: Update the data queue length based on (4), $\forall i, j$.
9: Update the energy queue length based on (6), $\forall j$.
10: **Until** $t = t_{\text{end}}$.
11: **end if**

B. PERFORMANCE ANALYSIS

In this subsection, we analyze the performance of the proposed DEPA algorithm, to showcase some important properties. When the channel state of each node is independent and identically distributed (i.i.d.), the following theorem can be obtained by using DEPA algorithm.

Theorem 1: a) The average data queue length is upper bounded as

$$\lim_{T\to\infty}\sup\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\left[\sum_{j=1}^{M}\sum_{i=1}^{N_j}Q_{ij}(t)\right] \leq \frac{\widetilde{A}+VR_{\max}}{\xi} \quad (22)$$

with

$$\widetilde{A} = A + \sum_{j=1}^{M}\theta_j\left(P_{\max}+\varepsilon_{\max}^{(\text{out})}\right) + \left(e_{\max}+\varepsilon_{\max}^{(\text{in})}\right)\sum_{j=1}^{M}\left(\theta_j+\varepsilon_{\max}^{(\text{in})}+e_{\max}\right),$$

where $R_{\max} \geq \mathbb{E}\left[\sum_{j=1}^{M}\sum_{i=1}^{N_j}R_{ij}(t)\right]$, and ξ is a positive finite value.

b) Let $E_{\max}$ represent BS's maximum battery capacity of storing energy, by setting the perturbation θ_j as

$$\theta_j = \theta = E_{\max} - \varepsilon_{\max}^{(\text{in})} - e_{\max}, \forall j, \quad (23)$$

the energy queue length is bounded by $0 \leq E_j(t) \leq E_{\max}, \forall t, j$.

Proof: a): Let the network capacity region Λ denote the set of traffic arrival rate that can be supported stably. Assuming that the average arrival rate is strictly interior to

Λ, then, there exists a stationary randomized algorithm to achieve [32]

$$\mathbb{E}\left[R_{ij}^{\mathrm{ALT}}(t)\right] \geq \mathbb{E}\left[D_{ij}(t)\right] + \xi, \tag{24}$$

where $R_{ij}^{\mathrm{ALT}}(t)$ is the data rate under this algorithm, $\mathbb{E}\left[D_{ij}(t)\right] + \xi \in \Lambda$, and ξ is a positive finite value. Note that (24) is commonly used for examining the network stability [32], which indicates that each user's average data rate is larger than its average traffic arrival rate. Since the aim of DEPA algorithm is to minimize the RHS of (11) under C3-C5 constraints, we first have

$$\begin{aligned}
&\Delta_V(t) \\
&\leq A - \sum_{j=1}^{M}\sum_{i=1}^{N_j} Q_{ij}(t)\,\mathbb{E}\left[\left(R_{ij}^{\mathrm{ALT}}(t) - D_{ij}(t)\right) \mid Z(t)\right] \\
&\quad + \sum_{j=1}^{M}\left(E_j(t) - \theta_j\right)\mathbb{E}\left[e_j^{\mathrm{ALT}}(t) \mid Z(t)\right] \\
&\quad - \sum_{j=1}^{M}\left(E_j(t) - \theta_j\right)\mathbb{E}\left[P_j^{\mathrm{ALT}}(t) + \sum_{j'=1, j'\neq j}^{M} \varepsilon_{jj'}^{\mathrm{ALT}}(t) \mid Z(t)\right] \\
&\quad + \sum_{j=1}^{M}(E_j(t) - \theta_j)\mathbb{E}\left[\sum_{j'=1, j'\neq j}^{M} \beta\varepsilon_{j'j}^{\mathrm{ALT}}(t) \mid Z(t)\right] \\
&\quad - V\mathbb{E}\left[\sum_{j=1}^{M}\sum_{i=1}^{N_j} R_{ij}^{\mathrm{ALT}}(t) \mid Z(t)\right],
\end{aligned} \tag{25}$$

where $R^{\mathrm{ALT}}(t)$, $J^{\mathrm{ALT}}(t)$, $e^{\mathrm{ALT}}(t)$, $P^{\mathrm{ALT}}(t)$, $\boldsymbol{\varepsilon}^{\mathrm{ALT}}(t)$ represent the control decisions under the alternative algorithm satisfying (24). In light of boundedness of parameters and (24), $\Delta_V(t)$ satisfies

$$\begin{aligned}
\Delta_V(t) &\leq A - \xi\sum_{j=1}^{M}\sum_{i=1}^{N_j} Q_{ij}(t) + \left(e_{\max} + \varepsilon_{\max}^{(\mathrm{in})}\right)\sum_{j=1}^{M} E_j(t) \\
&\quad + \sum_{j=1}^{M}\theta_j\left(P_{\max} + \varepsilon_{\max}^{(\mathrm{out})}\right) - V\mathbb{E}\left[\sum_{j=1}^{M}\sum_{i=1}^{N_j} R_{ij}^{\mathrm{ALT}}(t) \mid Z(t)\right].
\end{aligned} \tag{26}$$

By taking expectations over $Z(t)$ and using telescoping sums over $t = 0, \ldots, T-1$ with respect to (26), we have

$$\begin{aligned}
&\mathbb{E}\left[L(T) - L(0)\right] - V\sum_{t=0}^{T-1}\mathbb{E}\left[\sum_{j=1}^{M}\sum_{i=1}^{N_j} R_{ij}(t)\right] \\
&\leq T\left(A + \sum_{j=1}^{M}\theta_j\left(P_{\max} + \varepsilon_{\max}^{(\mathrm{out})}\right)\right) \\
&\quad - \xi\sum_{t=0}^{T-1}\mathbb{E}\left[\sum_{j=1}^{M}\sum_{i=1}^{N_j} Q_{ij}(t)\right] + \left(e_{\max} + \varepsilon_{\max}^{(\mathrm{in})}\right) \\
&\quad \times \sum_{t=0}^{T-1}\mathbb{E}\left[\sum_{j=1}^{M} E_j(t)\right] - V\sum_{t=0}^{T-1}\mathbb{E}\left[\sum_{j=1}^{M}\sum_{i=1}^{N_j} R_{ij}^{\mathrm{ALT}}(t)\right].
\end{aligned} \tag{27}$$

Based on the energy harvesting decision of the DEPA algorithm, BS j will not harvest renewable energy at time t, if $E_j(t) > \theta_j$. In this case, BS j may still seek to receive the transferred energy from other BSs, but the transferred energy will be completely consumed for increasing data rate at this time slot, to minimize the upper bound of the drift-plus-penalty. As such, $E_j(t) \leq \theta_j + \varepsilon_{\max}^{(\mathrm{in})} + e_{\max}, \forall t, j$. Therefore, by considering (27) and $\mathbb{E}[L(t)] > 0$, we can further obtain

$$\begin{aligned}
&\xi\sum_{t=0}^{T-1}\mathbb{E}\left[\sum_{j=1}^{M}\sum_{i=1}^{N_j} Q_{ij}(t)\right] \\
&\quad \leq T\left(A + \sum_{j=1}^{M}\theta_j\left(P_{\max} + \varepsilon_{\max}^{(\mathrm{out})}\right)\right) + \mathbb{E}\left[L(0)\right] \\
&\qquad + \left(e_{\max} + \varepsilon_{\max}^{(\mathrm{in})}\right)\sum_{t=0}^{T-1}\mathbb{E}\left[\sum_{j=1}^{M} E_j(t)\right] \\
&\qquad + V\sum_{t=0}^{T-1}\mathbb{E}\left[\sum_{j=1}^{M}\sum_{i=1}^{N_j} R_{ij}(t)\right].
\end{aligned} \tag{28}$$

By dividing both sides by ξT and taking a limit as $T \to \infty$, we obtain (22) and complete the proof.

b): Since $E_j(0) \geq 0$ at the beginning time, according to (5) and (6), we have $E_j(t+1) \geq e_j(t) \geq 0, \forall j$. Hence $E_j(t) \geq 0, \forall t, j$. From (a), we note that $E_j(t) \leq \theta_j + \varepsilon_{\max}^{(\mathrm{in})} + e_{\max}, \forall t, j$, thus $E_j(t) \leq E_{\max}, \forall t, j$. This completes the proof. □

From **Theorem** 1, we find that the proposed DEPA algorithm satisfies the network stability, and prevents the renewable energy overflow by selecting appropriate value of θ_j under BS's battery constraint.

IV. SIMULATION RESULTS

In this section, numerical results are presented to demonstrate the performance of the proposed DEPA algorithm in subsection III-A. We also give comparisons by considering the cases with/without energy cooperation. For the case without energy cooperation, each power control decision in the DEPA algorithm is obtained by using CVX [33] to solve problem (21) with $\varepsilon_{jj'} = 0, \forall j, j'$. Our theoretical analysis is independent of the specific spatial distributions of BSs and UEs. In the simulation, we assume that each user's data arrival rate follows an independent homogeneous poisson point process with the same mean value λ as $\lambda = 0.5$ bits/slot/Hz for the sake of simplicity. Note that our model and proposed algorithm are also applied to the scenario with heterogeneous data arrival rate distributions. The energy harvesting process E_j at BS j is modeled as a stationary stochastic process with the probability density function $f_j(z_j) = 1/(b_j - a_j), \forall z_j \in [a_j, b_j]$ where a_j and b_j is the minimum and maximum harvested energy of BS j respectively [34]. The system-level channel model and basic parameters are illustrated in Table I, and the number of BSs, energy transfer efficiency, and the selected perturbation will be detailed in the following simulation results. In addition, we run the Monte Carlo simulation for $T = 5000$ time slots in the Matlab software environment.

TABLE 1. Simulation parameters.

Parameter	Value
BS layout	Hexagonally arranged cell sites
UE layout	Uniformly located in area with 3 active UEs per BS cell
Inter site distance	200 m
Bandwidth (B)	1 GHz
Carrier frequency of mmWave small cell	28 GHz
Thermal Noise power	-174 dBm/Hz+10 $\log_{10}$ (B) +noise figure of 7 dB
Path loss of mmWave BS	$\alpha + 10\eta\log_{10}d(m) + \xi$ $\xi \sim \mathcal{N}(0, \sigma^2)$, LOS :$\alpha = 61.4, \eta = 2,$ $\sigma = 5.8$ dB; NLOS :$\alpha = 72.0,$ $\eta = 2.92, \sigma = 8.7$ dB [30]
Probability of Outage(O)-LOS-NLOS in mmWave small cell	O: $P_o(d) = \max\{0, 1 - e^{-\frac{d}{30}+5.2}\}$; LOS: $p_L(d) = (1 - P_o(d))e^{-\frac{d}{67.1}}$; NLOS: $1 - P_o(d) - p_L(d)$ [30]
Maximum transmit power of BS	40 dBm
Log-normal shadowing fading	10 dB
Antenna gain of BS	18 dB
Antenna gain of UE	0 dB
Min harvested power	a_j = [0, 20] dBm
Max harvested power	b_j = [20, 40] dBm

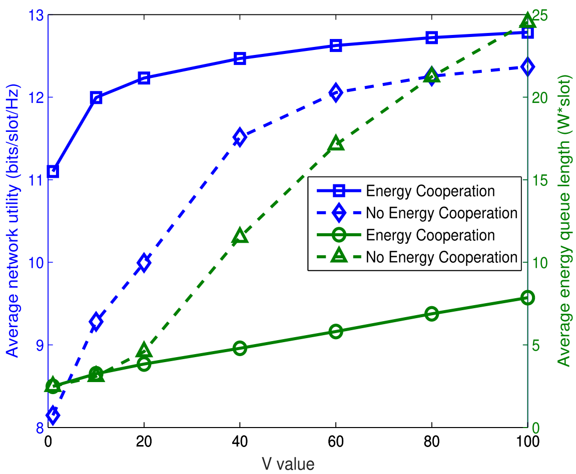


FIGURE 2. Average network utility and energy queue length versus V value.

Fig. 2 shows the average network utility and energy queue versus V values. The number of BSs is 7, $\beta = 0.9$, and $\theta = V$. We observe that both the average network utility and the average energy queue length increase with V. By using the proposed DEPA algorithm, the average network utility quickly approaches an optimal value. For the same V, the average network utility under energy cooperation is much better than that without energy cooperation. More importantly, using energy cooperation, the amount of energy in the queue is much lower, which indicates that energy cooperation has the ability to relieve the demand for large battery capacity at the BSs. The reason is that without energy cooperation, each BS has to store more its harvested energy and use it during the time slots when the harvested energy is insufficient, on the contrary, energy cooperation allows that BS can borrow energy from BSs with extra harvested energy at each time slot and BSs do not need to store large amount of harvested energy for supporting following transmissions.

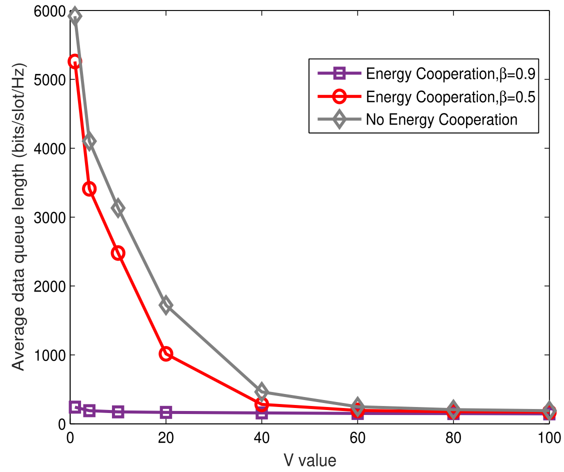


FIGURE 3. Average data queue length versus *V* value.

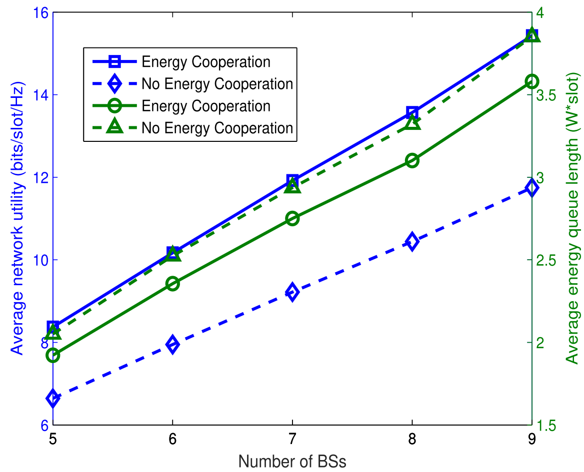


FIGURE 4. Average network utility and energy queue length versus the number of BSs.

Fig. 3 shows the average data queue length versus V values. The number of BSs is 7, and $\theta = V$. We see that when V is not large($V < 60$ in this figure), the size of average data queue under energy cooperation is much lower than that without energy cooperation, which indicates that the use of energy cooperation has the advantage of reducing delay. When V grows large, the average data queue length without energy cooperation is close to that under energy cooperation. The reason is that as shown in Fig. 1, the average network utility increases with V, which decreases the amount of waiting data. We note that in order to reduce the delay, large V is needed for no energy cooperation case, which results in the requirement of large battery capacity at BSs as seen in Fig. 1. Meanwhile, when the energy transfer efficiency β is larger, the average data queue of BSs is shorter, which means less data is blocked.

Fig. 4 displays the average network utility and energy queue length versus BS number. We choose $V = 100$, $\beta = 0.9$, and $\theta = 20$. It is observed that the average network utility increases with the BS number. The utility gap between with/without energy cooperation is expanded with increasing BS number. That's because when more BSs are

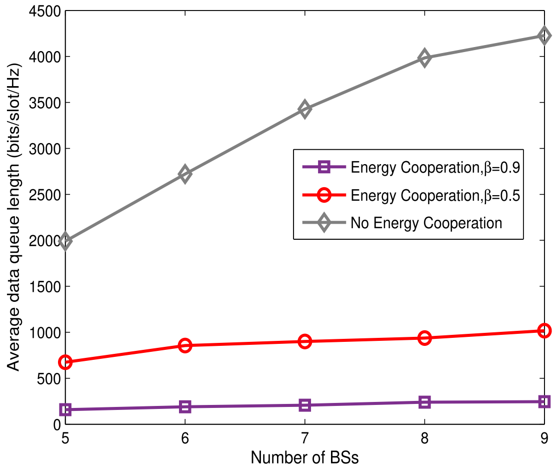


FIGURE 5. Average data queue length versus the number of BSs.

deployed, more energy can be shared between BSs, which can support higher utility and reduce the demand for large battery capacity. Meanwhile, as mentioned in Fig. 2, the average energy queue length of the network with energy cooperation is lower than the network without energy cooperation.

Fig. 5 illustrates the average data queue length versus the BS number with $V = 100$ and $\theta = 20$. We see that the average data queue length increases with the BS number, due to more user services being provided. When adding more BSs, the length of the average data queue with energy cooperation increases much more slowly than the data queue without energy cooperation. This can be explained by the fact that when the BS number is larger, under the same data traffic arrival rate, the increase of the network utility with energy cooperation is much greater than the case of no energy cooperation, which in turn substantially reduce the growth rate of data queue length.

V. CONCLUSION

In this paper, we studied power control in energy cooperation enabled downlink mmWave cellular networks with renewable energy harvesting. We formulated a stochastic optimization problem, to maximize the time average network utility and control the data queue and energy queue. Based on Lyapunov optimization, We develop an online algorithm called DEPA to solved the formulated problem. We confirmed that the proposed algorithm can ensure the stability of networks and prevent renewable energy overflow by selecting an appropriate value of perturbation used in Lyapunov function. The results showed that compared with the system without energy cooperation, the proposed algorithm with energy cooperation can maximize the network utility while keeping the data and energy queue lengths at a low level.

In this work, we assume that the interference between BSs can be negligible as mentioned in [28] and [29], due to fact that the mmWave cellular networks tend to be noise-limited when it is not ultra-dense. However, in ultra-dense mmWave networks, interference may still be severe [35]. Therefore, resource allocation in energy cooperation enabled dense mmWave networks is needed to be investigated, which will be our future work. In addition, here, we assume that UEs of the same BS share the frequency resources with equal assignment, and the transmit power of each UE data stream in a cell is identical. Note that it is an important work to study the more complicated case of the power allocation among different UEs of the same BS, which depends on both channel state information and UE's data queue length.

REFERENCES

[1] *Cisco Internet Business Solutions Group (IBSG)*. [Online]. Available: http://www.cisco.com/c/dam/en_us/about/ac79/docs/innov/IoT_IBSG_0411FINAL.pdf

[2] D. Jiang, P. Zhang, Z. Lv, and H. Song, "Energy-efficient multi-constraint routing algorithm with load balancing for smart city applications," *IEEE Internet Things J.*, vol. 3, no. 6, pp. 1437–1447, Dec. 2016

[3] T. Han and N. Ansari, "Powering mobile networks with green energy," *IEEE Wireless Commun.*, vol. 21, no. 1, pp. 90–96, Feb. 2014.

[4] O. Ozel, K. Tutuncuoglu, J. Yang, S. Ulukus, and A. Yener, "Transmission with energy harvesting nodes in fading wireless channels: Optimal policies," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 8, pp. 1732–1743, Sep. 2011.

[5] F. M. Ozcelik, G. Uctu, and E. Uysal-Biyikoglu, "Minimization of transmission duration of data packets over an energy harvesting fading channel," *IEEE Commun. Lett.*, vol. 16, no. 12, pp. 1968–1971, Dec. 2012.

[6] J. Yang and S. Ulukus, "Optimal packet scheduling in an energy harvesting communication system," *IEEE Trans. Commun.*, vol. 60, no. 1, pp. 220–230, Jan. 2012.

[7] P. He, L. Zhao, S. Zhou, and Z. Niu, "Recursive waterfilling for wireless links with energy harvesting transmitters," *IEEE Trans. Veh. Technol.*, vol. 63, no. 3, pp. 1232–1241, Mar. 2014.

[8] C. Huang, R. Zhang, and S. Cui, "Optimal power allocation for outage probability minimization in fading channels with energy harvesting constraints," *IEEE Trans. Wireless Commun.*, vol. 13, no. 2, pp. 1074–1087, Feb. 2014.

[9] C. K. Ho and R. Zhang, "Optimal energy allocation for wireless communications with energy harvesting constraints," *IEEE Trans. Signal Process.*, vol. 60, no. 9, pp. 4808–4818, Sep. 2012.

[10] J. Lei, R. Yates, and L. Greenstein, "A generic model for optimizing single-hop transmission policy of replenishable sensors," *IEEE Trans. Wireless Commun.*, vol. 8, no. 2, pp. 547–551, Feb. 2009.

[11] M. Nourian, A. S. Leong, and S. Dey, "Optimal energy allocation for Kalman filtering over packet dropping links with imperfect acknowledgments and energy harvesting constraints," *IEEE Trans. Autom. Control*, vol. 59, no. 8, pp. 2128–2143, Aug. 2014.

[12] J. Yang and S. Ulukus, "Optimal packet scheduling in a multiple access channel with energy harvesting transmitters," *J. Commun. Netw.*, vol. 14, no. 2, pp. 140–150, Apr. 2012.

[13] Z. Wang, V. Aggarwal, and X. Wang, "Iterative dynamic water-filling for fading multiple-access channels with energy harvesting," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 382–395, Mar. 2015.

[14] J. Yang, O. Ozel, and S. Ulukus, "Broadcasting with an energy harvesting rechargeable transmitter," *IEEE Trans. Wireless Commun.*, vol. 11, no. 2, pp. 571–583, Feb. 2012.

[15] X. Zhang, Z. Zheng, Q. Shen, J. Liu, X. S. Shen, and L.-L. Xie, "Optimizing network sustainability and efficiency in green cellular networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 2, pp. 1129–1139, Feb. 2014.

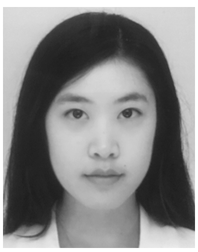
[16] T. Han and N. Ansari, "On optimizing green energy utilization for cellular networks with hybrid energy supplies," *IEEE Trans. Wireless Commun.*, vol. 12, no. 8, pp. 3872–3882, Aug. 2013.

[17] D. W. K. Ng, E. S. Lo, and R. Schober, "Energy-efficient resource allocation in OFDMA systems with hybrid energy harvesting base station," *IEEE Trans. Wireless Commun.*, vol. 12, no. 7, pp. 3412–3427, Jul. 2013.

[18] J. Gong, J. S. Thompson, S. Zhou, and Z. Niu, "Base station sleeping and resource allocation in renewable energy powered cellular networks," *IEEE Trans. Commun.*, vol. 62, no. 11, pp. 3801–3813, Nov. 2014.

[19] Y. Cui, V. K. N. Lau, and Y. Wu, "Delay-aware BS discontinuous transmission control and user scheduling for energy harvesting downlink coordinated MIMO systems," *IEEE Trans. Signal Process.*, vol. 60, no. 7, pp. 3786–3795, Jul. 2012.

[20] T. Han and N. Ansari, "Green-energy aware and latency aware user associations in heterogeneous cellular networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2013, pp. 4946–4951.
[21] M. Ismail and W. Zhuang, "Green radio communications in a heterogeneous wireless medium," *IEEE Wireless Commun.*, vol. 21, no. 3, pp. 128–135, Jun. 2014.
[22] Y. Guo, J. Xu, L. Duan, and R. Zhang, "Joint energy and spectrum cooperation for cellular communication systems," *IEEE Trans. Commun.*, vol. 62, no. 10, pp. 3678–3691, Oct. 2014.
[23] B. Gurakan, O. Ozel, J. Yang, and S. Ulukus, "Energy cooperation in energy harvesting communications," *IEEE Trans. Commun.*, vol. 61, no. 12, pp. 4884–4898, Dec. 2013.
[24] J. Xu, L. Duan, and R. Zhang, "Cost-aware green cellular networks with energy and communication cooperation," *IEEE Commun. Mag.*, vol. 53, no. 5, pp. 257–263, May 2015.
[25] J. Xu and R. Zhang, "CoMP meets smart grid: A new communication and energy cooperation paradigm," *IEEE Trans. Veh. Technol.*, vol. 64, no. 6, pp. 2476–2488, Jun. 2015.
[26] S. Lakshminarayana, T. Q. S. Quek, and H. V. Poor, "Cooperation and storage tradeoffs in power grids with renewable energy resources," *IEEE J. Sel. Area Commun.*, vol. 32, no. 7, pp. 1386–1397, Jul. 2014.
[27] M. J. Neely, "Energy optimal control for time-varying wireless networks," *IEEE Trans. Inf. Theory*, vol. 52, no. 7, pp. 2915–2934, Jul. 2006.
[28] J. G. Andrews *et al.*, "What will 5G be?" *IEEE J. Sel. Areas Commun.*, vol. 32, no. 6, pp. 1065–1082, Jun. 2014.
[29] D. Li, W. Saad, and C. S. Hong, "Decentralized renewable energy pricing and allocation for millimeter wave cellular backhaul," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1140–1159, May 2016.
[30] M. R. Akdeniz *et al.*, "Millimeter wave channel modeling and cellular capacity evaluation," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 6, pp. 1164–1179, Jun. 2014.
[31] L. Huang and M. J. Neely, "Utility optimal scheduling in energy-harvesting networks," *IEEE/ACM Trans. Netw.*, vol. 21, no. 4, pp. 1117–1130, Aug. 2013.
[32] M. J. Neely, *Stochastic Network Optimization With Application to Communication and Queueing Systems*. San Rafael, CA, USA: Morgan & Claypool, 2010.
[33] M. Grant and S. Boyd. (Apr. 2011). *CVX: MATLAB Software for Disciplined Convex Programming, Version 1.21*. [Online]. Available: http://cvxr.com/cvx/
[34] M. Zheng, P. Pawelczak, S. Stanczak, and H. Yu, "Planning of cellular networks enhanced by energy harvesting," *IEEE Commun. Lett.*, vol. 17, no. 6, pp. 1092–1095, Jun. 2013.
[35] T. Bai and R. W. Heath, Jr., "Coverage and rate analysis for millimeter-wave cellular networks," *IEEE Trans. Wireless Commun.*, vol. 14, no. 2, pp. 1100–1114, Feb. 2015.



BINGYU XU received the B.Sc. degrees in telecommunications engineering with management from the Beijing University of Posts and Telecommunications, China, and the Queen Mary University of London, U.K., in 2014. She is currently pursuing the Ph.D. degree in electronic engineering with the Queen Mary University of London, London, U.K. Her current research interests include radio resource allocation optimization in HetNets, co-operative wireless networking, millimeter wave, and smart energy systems.

YUE CHEN (S'02–M'03–SM'15) received the Ph.D. degree from the Queen Mary University of London (QM), London, U.K., in 2003. She is currently a Professor of Telecommunications Engineering with the School of Electronic Engineering and Computer Science, QM. Her current research interests include intelligent radio resource management for wireless networks, MAC and network layer protocol design, cognitive and co-operative wireless networking, HetNets, smart energy systems, and Internet of Things.

JESÚS REQUENA CARRIÓN (S'02–M'03–SM'15) received the degree in telecommunication engineering and the Ph.D. degree in multimedia and telecommunications engineering from the Carlos III University of Madrid in 2003 and 2008, respectively. He is currently a Lecturer (Assistant Professor) with the School of Electronic Engineering and Computer Science, Queen Mary University of London. His main research interests include statistical signal processing and computer modeling and simulation of complex systems.

JONATHAN LOO (M'01) received the M.Sc. degree (Hons.) in electronics and the Ph.D. degree in electronics and communications from the University of Hertfordshire, Hertfordshire, U.K., in 1998 and 2003, respectively. From 2003 to 2010, he was a Lecturer in multimedia communications with the School of Engineering and Design, Brunel University, Uxbridge, U.K. Since 2010, he has been a Reader in communication and networking with the School of Science and Technology, Middlesex University, London, U.K. He leads the Research Team in the area of communication and networking. His research interests include information centric networking, cloud computing, network architecture, communication protocols, wireless and mobile networks, network security, embedded systems, and digital signal processing. He has successfully graduated 16 Ph.D. students and co-authored over 200 both journal and conference papers in the aforementioned specialist areas. He was the Lead Editor of the book *Mobile Ad Hoc Networks: Current Status and Future Trends* (CRC Press, 2011). He has been an Associate Editor of the *Wiley International Journal of Communication Systems* since 2011.

ALEXEY VINEL (M'07–SM'12) received the bachelor's and master's degrees (Hons.) in information systems from the Saint-Petersburg State University of Aerospace Instrumentation, Russia, in 2003 and 2005, respectively, the Ph.D. degree in technology from the Institute for Information Transmission Problems, Russia, in 2007, and the Ph.D. degree in technology from the Tampere University of Technology, Finland, in 2013. He is currently a Professor of Computer Communications with the School of Information Technology, Halmstad University, Sweden. His research interests include vehicular networking, co-operative intelligent transportation systems, and autonomous driving. He has been an Associate Editor of the IEEE COMMUNICATIONS LETTERS since 2012, the IEEE WIRELESS COMMUNICATIONS since 2015, and the IEEE TRANSACTIONS ON DEPENDABLE AND SECURE COMPUTING since 2016.